Investigation of Long Term Forest Cover Change using Declassified Cold War Intelligence Imagery

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BACKGROUND

Historic Panchromatic Imagery for Land Cover Classification

- U.S. intelligence community initiated the Keyhole (KH) satellite program in 1959
- KH program was made up of multiple sensors, the imagery in this project is from the Hexagon (KH-9) series
- Beginning in the 1990s, the imagery has been declassified, providing a valuable archive for studying past landscapes

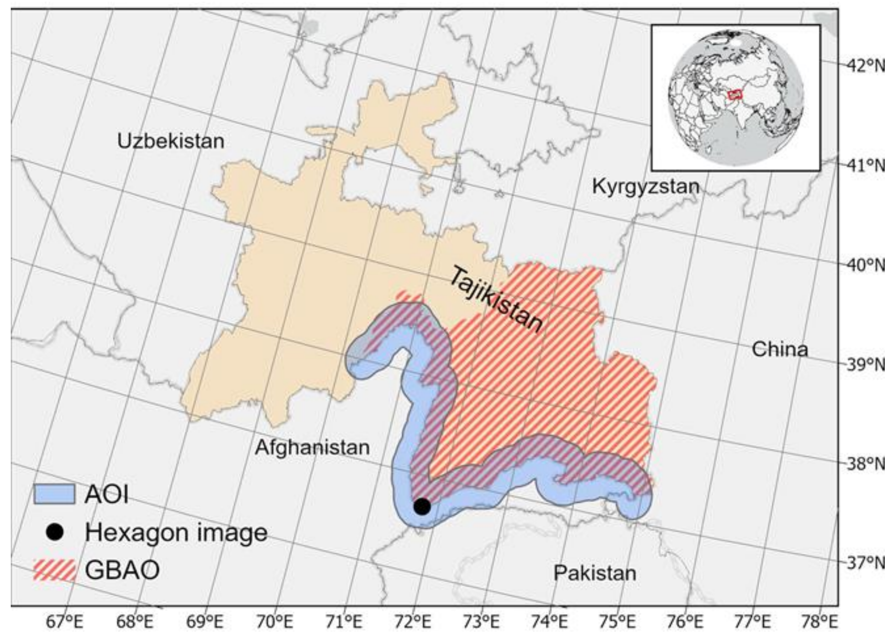
Study Area: Pamir Mountains, Tajikistan

High-elevation, mountainous environment

- Limited forest cover presents challenge of classifying highly unbalanced data
- Previous KH classification studies have been in areas with more forest coverage (e.g., Latvia, Caucasus)

Significant change in forest extent since Hexagon imagery was taken

- Under the Tajik Soviet Socialist Republic, USSR provided fuel subsidies and regulated forest harvesting (Haider et al.)
- Following the USSR's collapse and the blockade of Gorno-Badakhshan Autonomous Oblast (GBAO) during the Tajik Civil War (1992–1997), communities relied on forests for fuel



GOAL

Develop a method for classifying Hexagon imagery to detect historical land cover

- Part of a broader study that aims to analyze the impacts of conflict (Tajik Civil War) on landscape
- Area of interest for the broader study is a buffer along the border of GBAO and Afghanistan (see map above)
- Due to data availability, this project only analyzed a section of a Hexagon image covering 3,267 ha for method development

METHOD

A hybrid approach was developed to assess forest extent using historic panchromatic Keyhole imagery (June 1979) and modern multispectral PlanetScope imagery (September 2024)

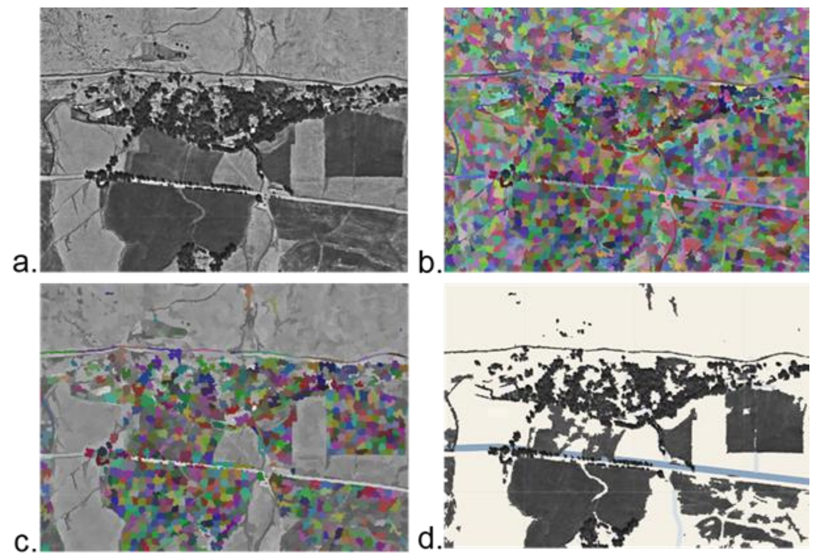
1 Segmentation and Masking

- Segmentation using Simple Non-Iterative Clustering (SNIC) in Google Earth Engine identified superpixels based on spatial proximity and pixel similarity
- Segments with mean pixel value less than a threshold were removed
- Remaining segments were used to mask the image for classification

2 Texture Metrics

Because classification utilizing spectral signatures cannot be applied to panchromatic imagery, I used a texture-based analysis (Rizayeva et al., Song et al.)

- Texture metrics (contrast, dissimilarity, homogeneity, angular second moment, entropy, mean, variance, and sum average) were calculated using a 3x3, 7x7, and 11x11 moving window
- The metrics, along with slope data, were combined into a multi-layer raster and normalized using z-score normalization



Segmentation process: (a) panchromatic image, (b) SNIC segments, (c) segments are filtered by mean pixel value of the image, and (d) original image is masked by segments whose mean pixel value is greater than 90 (d).

3 Random Forest Classification

- Training data for the classification was derived from segmented polygons representing six land cover classes: barren, water, shadow, forest, agricultural, and herbaceous
- A Random Forest model was trained on the multi-layer raster and applied to classify the image

4 PlanetScope Classification

- A supervised Random Forest classifier was applied to the multispectral imagery, utilizing the spectral signatures of the classes

5 Change Over Time

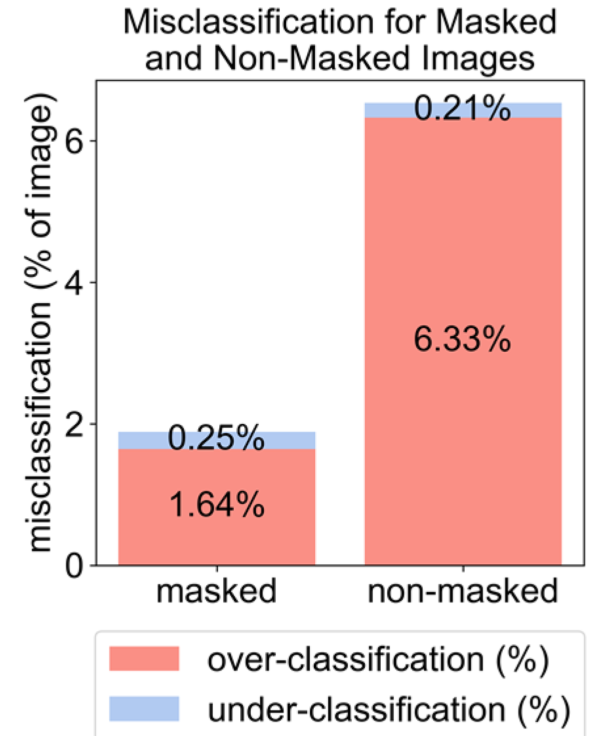
- PlanetScope imagery (3 m resolution) was resampled to Hexagon resolution (0.93 m)
- Pixel-wise comparison to estimate change in forest extent

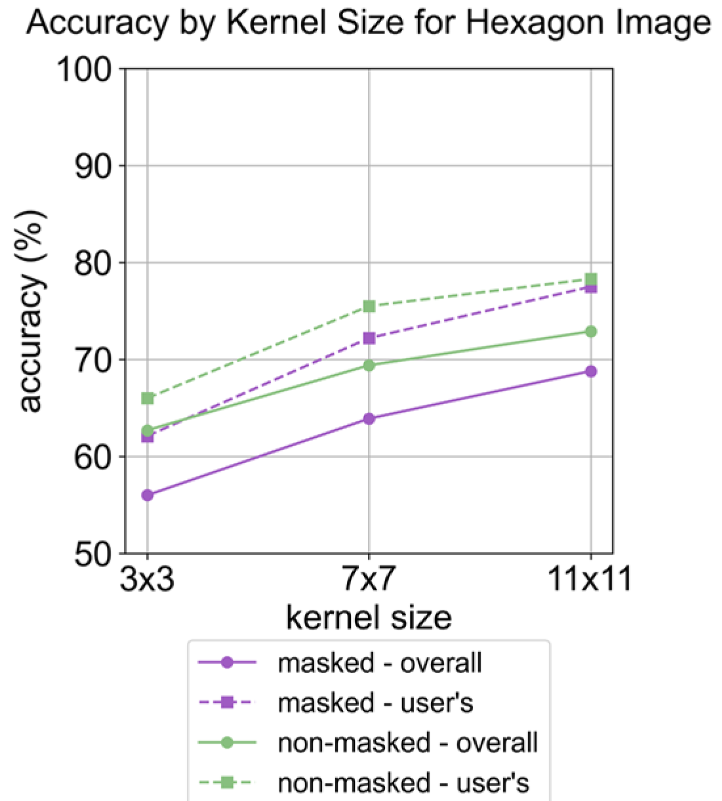
RESULTS

1 Panchromatic Imagery Classification

Misclassification

- I classified the Hexagon image through visual interpretation to quantify over-classification (false positives) and under-classification (false negatives)
- Compared to classifying the entire image, over-classification (non-forest areas labeled as forest) was reduced by masking the image using SNIC segments
- Under-classification was low in both methods





Texture metric evaluation: 3x3, 7x7, and 11x11 window size were tested, with accuracy increasing as the window size increased

- Larger window sizes (e.g., 11×11) led to higher user's accuracy for the forest class, indicating that fewer non-forest areas were incorrectly classified as forest
- The masked image classification performed similarly to the whole image, showing minimal negative impact from masking

2 PlanetScope Imagery Classification

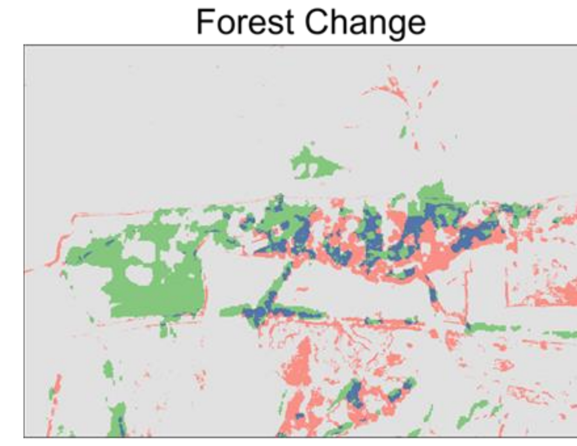
PlanetScope classification accuracy outperformed Hexagon due to better spectral resolution

- 84.7% overall accuracy, 95.8% user's accuracy

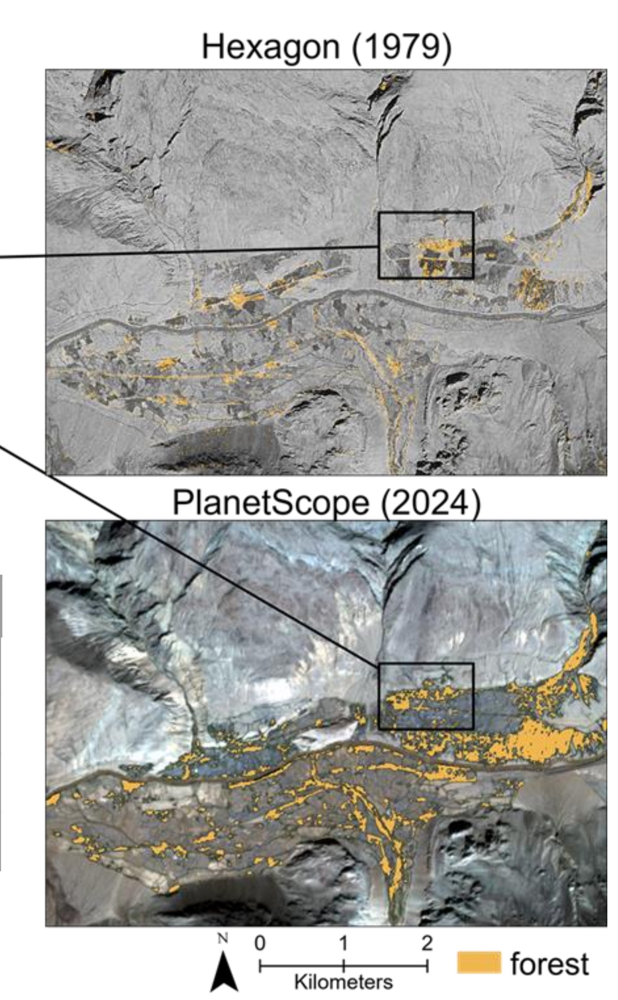
3 Change Detection

Change raster shows forest gain and loss. Notable gains were observed across the area, though misclassifications in the Hexagon image may have overestimated loss in certain areas.

Forest Change



class	hectares	% of image
stable non-forest	3064.78	93.82
gain	126.81	3.88
loss	55.2	1.69
stable forest	19.8	0.61



CONCLUSIONS

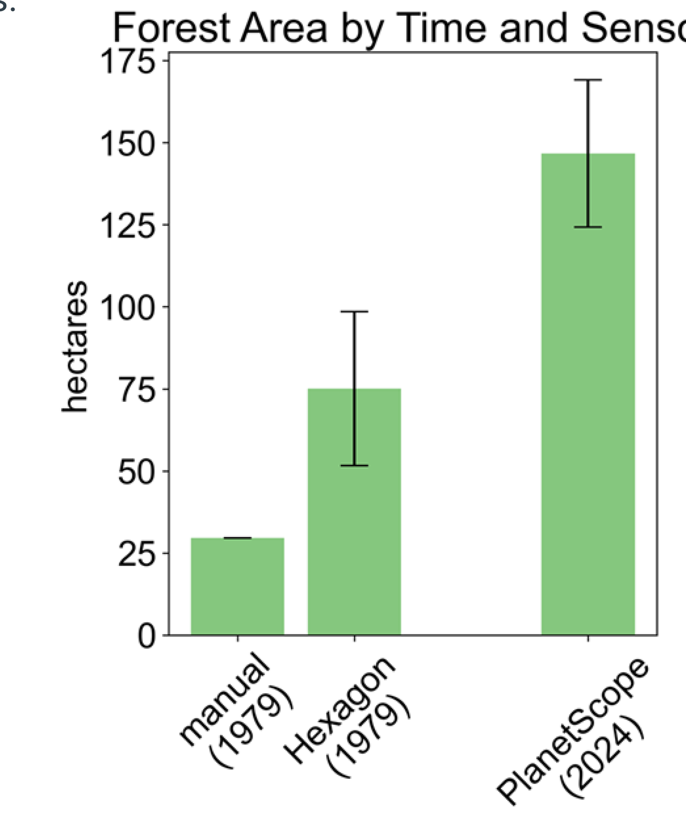
Successfully classified forest extent in historic Hexagon and modern PlanetScope imagery, demonstrating significant increase in forest cover between 1979 and 2024

- Classification was effective but prone to over-classifying forest coverage
- Masking image by mean segment value mitigates this challenge
- Larger kernel size improved classification accuracy, though optimal size may vary by landscape and dataset

Limitations and Future Directions:

- For Hexagon, the difference between manual classification area and measured error in methodology shows that there are sources of error that were not captured in accuracy assessments
- Expanding training data and exploring object-based classification could improve accuracy
- Further analysis using additional imagery between end of Tajik Civil War and present could refine understanding of forest change, especially in relation to conflict

Broader Impact: Provides a scalable framework for studying long-term land cover change using historical satellite imagery, with potential applications in environmental and conflict studies.



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